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ADJUSTING TO RANDOM DEMANDS OF PATIENT CARE: A PREDICTIVE MODEL FOR NURSING STAFF SCHEDULING AT NAVAL MEDICAL CENTER SAN DIEGO

by

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September 2008

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In this thesis, time series methods were used to forecast the monthly number of nursing Full Time Equivalents (FTEs) required to meet patient care needs at Naval Medical Center San Diego. In order to capture both patient census and patient acuities, the monthly total required workload hours given by the Res-Q system was used. The monthly number of nursing FTEs was calculated by dividing the total monthly workload hours required by 168 hours (per DoD 6010.13-M). The Holt-Winters' time series models were fit using both Excel and JMP software packages. Using three years of historical data to fit the models, the number of nursing FTEs that would be required every month for the fiscal year 2008 for the entire hospital was forecasted with a Mean Absolute Percentage Error (MAPE) of 17.83. Fitting the model to data starting from December 2005, to eliminate historical anomalies, further reduced the MAPE to 8.80. The overall model was, subsequently, partitioned into five sub-models, one for each of the five nursing units, reflecting the hospital's patient and nursing staff mixes. Again after adjusting for missing data points and outliers, the monthly number of nursing FTEs required for 4West, Adult ICU, Surgical, Medical, and Medical Oncology were forecasted with MAPE's of 20.77, 11.42, 13.63, 13.85, and 6.98, respectively.

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ADJUSTING TO RANDOM DEMANDS OF PATIENT CARE: A PREDICTIVE MODEL FOR NURSING STAFF SCHEDULING AT NAVAL MEDICAL CENTER SAN DIEGO

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In this thesis, time series models were used to forecast the monthly number of nursing Full Time Equivalents (FTEs) required to meet patient care needs at Naval Medical Center San Diego. In order to capture both patient census and patient acuities, the monthly total required workload hours given by the Res-Q system was used. The monthly number of nursing FTEs was calculated by dividing the total monthly workload hours required by 168 hours (per DoD 6010.13-M). The Holt-Winters' time series models were fit using both Excel and JMP software packages. Using three years of historical data to fit the models, the number of nursing FTEs that would be required every month for the fiscal year 2008 for the entire hospital was forecasted with a Mean Absolute Percentage Error (MAPE) of 17.83. Fitting the model to data starting from December 2005, to eliminate historical anomalies, further reduced the MAPE to 8.80. The overall model was, subsequently, partitioned into five sub-models, one for each of the five nursing units, reflecting the hospital's patient and nursing staff mixes. Again after adjusting for missing data points and outliers, the monthly number of nursing FTEs required for 4West, Adult ICU, Surgical, Medical, and Medical Oncology were forecasted with MAPE's of 20.77, 11.42, 13.63, 13.85, and 6.98, respectively.

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EXECUTIVE SUMMARY

Like many other hospitals in the nation, the Naval Medical Center San Diego (NMCSD) faces the problem of anticipating the right number of nursing staff Full Time Equivalents (FTEs) that will be needed every month to adequately meet patient care demands while minimizing the likelihood of overstaffing costs. The problem is further complicated because the hospital's nursing staff is comprised of several different groups of nurses, including the active duty nurses who perform their military obligations on top of their patient care job. Because of these obligations, which include physical readiness, command collateral duties, and deployment, military nurses may spend a good part of their time working either on non-patient care related matters or they may be away on deployment rather than being in the hospital. As a result, when patient censuses unexpectedly increase, the nursing administrators use contract nursing agencies to supply nurses to fill gaps.

To assist NMCSD management with nurse staffing planning, we fit Holt-Winter's time series models to historical patient demand data. Using three years of data to fit the models, the number of nursing FTEs required every month for the fiscal year 2008 for the entire hospital was forecasted with a Mean Absolute Percentage Error (MAPE) of 17.83. Fitting the model to data starting from December 2005, to eliminate historical anomalies, further reduced the MAPE to 8.80.

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I. INTRODUCTION

A. OVERVIEW

The technological changes experienced by the United States health care system have greatly impacted the delivery of health care, making it more effective in improving the lives of millions of patients. Yet these important changes have also affected various financial aspects of the health care system, such as changing the reimbursement of health care services from an out-of-pocket payment method by individual patients in the 1930's to the current standardized industry-based system of third-party payers. Reflecting on these changes, some researchers argue that the increasing discoveries in medical sciences have driven the reimbursement of health care services to an all time high and resulted in a change from retrospective payment system to a prospective payment system (Gallagher, 2002). According to a report by the Office of Evaluation and Inspections (OEI) of the Office of the Inspector General on the Medicare Hospital Prospective Payment System, Medicare expenditures rose from $4.7 billion in 1967 to $72.3 billion in 1985 (OEI, 2001). This huge increase in costs was determined by OEI to be due to the retrospective payment system, which reimbursed health care providers based on their charges for providing health care services and consequently motivated them to provide more services (OEI, 2001).

In order to counter this growth in health care costs, Congress enacted the Social Security Amendments in 1983, creating a prospective payment system (PPS) in which health care services are reimbursed based on a standardized cost system formerly known as diagnosis related groups (DRGs). In the late 1980s, a PPS system was adopted by the private insurance companies. In this system, health care services are reimbursed based on a capitation method in which providers are reimbursed a fixed amount for each hospital admission, regardless of the services provided or the length of stay (Gapenski, 1993).

Central to the delivery of health care services is the nursing staff whose skills and experience may contribute to the timely recovery of a patient, reducing inpatient length of stay. The nursing staff in a hospital represents one of the most vital entities in the delivery of health care, especially considering their roles and responsibilities for patients admitted both to the inpatient and outpatient settings. Nurses are responsible for implementing the treatment prescribed by physicians and in the process exercise a degree of independent assessment and judgment (Welton and Halloran, 2005). From the time of an inpatient admission to the time of discharge, at least one nurse is assigned to each patient's bedside and has a 24-hour direct accountability for the care of that patient (Welton et al., 2006). Nurses can impact patient outcomes, by their caring professionalism, their experience, their academic training, their levels of job satisfaction, and their workload (Aiken et al., 2002). Hence, one can argue that there is no effective delivery of health care services without a well trained and caring nursing staff.

However, hospital nursing care accounts for approximately one-quarter to one-third of the hospital operating budget and nearly half of all direct care costs (Kane & Siegrist, 2002; McCue, Mark, & Harless, 2003). The increased health care costs have affected all areas of the delivery of health care, including nursing services and nursing labor costs, and consequently prompted some researchers to suggest that the costs of nursing services should be calculated and reimbursed separately (Welton et al., 2006).

As with all types of employees, nurses generally perform better when they are satisfied with their jobs, and research suggests that two key job satisfaction factors for a nursing staff is scheduling and patient-to-nurse ratios, which in turn may positively influence patients' hospital length of stay. Two different studies by the American Nursing Associations (ANA) in 1992 and 1994 found an inverse relationship between hospital length of stay and total patient nursing hours. The first study reported that each additional hour of total nursing care per patient was associated with a decrease in expected length of stay of between 0.044 days and 0.097 days for hospitals in New York and Massachusetts. In the second study, it was found that registered nurse hours worked per patient was statistically and inversely associated with a reduction in length of stay (ANA, 1992 and 1994). Other areas where patient-to-nurse ratios reduce length of stay involve nursing services, such as cardiac step-down units (Shamian et al., 1994) and other medical units (Needleman et al., 2002).

In order to be able to do good patient-to-nurse ratio planning and scheduling, nursing administrators need to be able to anticipate future patient care requirements for their nursing units. Determining the right mix of a well-trained and caring nursing staff that will optimize the delivery of nursing care to the patients within the most cost effective way is quite challenging, especially with the current DRG reimbursement scheme, the rising cost of nursing labor (Embleton et al., 2007), and the fluctuations in patient census.

B. PROBLEM STATEMENT

Like many hospitals in the nation, Naval Medical Center San Diego (NMCSD) is faced with the problem of finding the best nursing staff model that that will reliably allow it to meet patient care requirements while minimizing nursing labor costs. However, unlike the civilian hospitals that may simply be faced with the problem of patient census fluctuations and daily adjustments of nursing staff schedules, the scheduling problem faced by NMCSD is more complex because of the different non-patient care obligations its military nurses have to perform aside from patient care. These obligations include standing duty, physical readiness exercises, command collateral duties, and deployment.

The goal of this thesis research is to develop a model that will allow the NMCSD nursing administrators to forecast the number of nurses that will be needed every month so that they can appropriate schedule their nursing staff, thereby minimizing the use of contract nursing hours and ultimately contract nursing labor costs.[1] The need for a model that will accurately predict the number of nurses required to meet patient care requirements is three-fold: (1) It

[1] From fiscal year 2005 to fiscal year 2007 NMCSD used 19,446 nursing contract hours, paying more than $1.2 million ($63*115.75FTE's*168hrs) for contract nurses.

will help take care of non-patient care requirements (standing duty, physical readiness exercises, and deployment) that military nurses have to perform; (2) it will allow for a better adjustment of patient workload and minimize nursing labor costs; and, (3) it will reduce possible staff burn out, and thereby increase patient safety.

II. BACKGROUND INFORMATION

This section provides some background information about Naval Medical Center San Diego, the types of nurses used in military hospitals, and a review of the literature on nursing staffing models. Additional background information explaining key medical terminology and acronyms is provided in the appendix.

A. NAVAL MEDICAL CENTER SAN DIEGO

NMCSD is a 266-bed tertiary care facility providing patient services ranging from same day surgery to brain surgery. The hospital serves a patient population made up of active duty service members, military retirees, eligible family members of the active duty service members and retirees, and injured patients from Operation Iraqi Freedom and Operation Enduring Freedom. Patients admitted to NMCSD receive world-class care via a rich mix of medical services that range from simple ambulatory visits to plastic surgery, neuro-surgery, general surgery, bariatric, ophthalmology, orthopedics, cardiology, thoracic surgery, vascular surgery, transient ischemic attack/cerebro vascular accident (TIA/CVA), OB/GYN, urology, non-infectious surgery, internal medicine, and medical ontology.

At NMCSD, the cost of nursing labor is mainly affected by fluctuations in daily patient census, the unavailability of civilian nurse employees after their normal working hours, the unavailability of military nurses due to military obligations, and the recourse to contract nurses by the nursing administrators to fill the gaps. For example, from August 2005 to June 2008, more 183 active duty registered nurses have been deployed from NMCSD in support of Operation Iraqi Freedom, Operation Enduring Freedom, and several other military supported disaster relief operations. As of April 2007, the United States Navy has deployed more than 750 nurses (Marino et al., 2007).

NMCSD also serves as a training facility for newly graduated nurses recruited into the hospital's nursing staff, giving them the opportunity to practice their academic knowledge under the supervision of experienced nurses and physicians. In the NMCSD accounting system, these new graduate nurses are counted as full-time equivalents and are indistinguishable from the other more experienced nursing personnel. However, because of their minimal work experience, the Res-Q system adjusts patient acuity levels to the maximum allowable nursing care hours per 24-hour period to make up for the time it takes an inexperienced nurse to care for a patient.

B. TYPES OF NURSES

The hospital's staff is comprised of four types of nurses:

1. Active Duty Nurse Officers

Active duty nurse officers have at least a bachelor's degree. Their responsibilities include both their patient care and non-patient care requirements, such as standing duty, theatre deployments, and physical readiness test (PRT) preparation. Those nurses may voluntarily assume other responsibilities, called collateral duties, which are mainly command-related.

2. Hospital Corpsmen

Hospital corpsmen are trained from one of the Naval Schools of Health Sciences and hold at least a high school diploma. Given their level of training, the Hospital Corpsmen function under the direct supervision of an active duty nurse officer, at the level of a licensed vocational nurse. Like the active duty nurses, they too can be deployed at any time and must complete other military duties such as standing watch, PRT preparation, and are required to perform command-related collateral duties.

3. Government Service (GS) Nurses

Government service (GS) nurses hold either a licensed vocational or a registered nurse license. Unlike the active duty nurses and the corpsmen, as civilians GS nurses are only responsible for direct patient care. However just like the active duty nurses and the corpsmen, the hospital has to account for their holiday, vacation, and sick times.

4. Contract Nurses

Contract agency nurses are sent to work at the hospital by their agency employers under a well-stipulated contact with the hospital. They hold either a licensed vocational or a registered nurse license. They are only responsible for direct patient care and patient care documentations. This group is quite small compared to the other three groups of nurses.

Due to the complexity of anticipating in the number of nurses that will be deployed, the military duties that (non-deployed) active duty nurses will have to perform, and the constraints on hiring new nursing personnel, when patient censuses are higher than expected the hospital must resort to using contract nurses to fill in gaps. Contract nurses are paid from the hospital's budget and their direct cost to NMCSD is almost twice that of active duty and GS nurses.

C. LITERATURE REVIEW: EFFECTS OF NURSE STAFFING

According to a study by Clark and colleagues, nurses with fewer resources, less leadership, lower staffing, and higher levels of emotional exhaustion are three times more likely to experience needle stick injuries (Clark et al., 2002). Nurses that feel satisfied with their jobs are more likely to effectively perform all the requirements of their duties, including good patient care documentations, increasing patient safety.

Research literature on nurse staffing has considered the impact of patient-to-nurse ratios on patient outcomes, nurse employee satisfactions, length of stay, and the staffing costs of nursing units. A nursing staff mixed with a greater level of registered nurses combined with a lower patient-to-nurse ratio is believed to contribute to improved patient care and decrease patient length of stay, resulting into direct benefits to hospitals (Flood and Diers, 1998; Needleman et al., 2202; Schultz et al., 1998).

The patient-to-nurse ratio can play a big role in nurse job satisfaction, nurse burnout, and patient health outcomes. In their studies on the effects of hospital nurse staffing and patient-to-nurse ratios on patient outcomes and nurse job satisfaction, Aiken and her colleagues found that "In hospitals with high patient-to-nurse ratios, surgical patients experience higher risk-adjusted 30-day mortality and failure-to-rescue rates and nurses are more likely to experience burnout and job dissatisfaction" (Aiken et al., 2002).

Accurately anticipating patient censuses is not an easy task. Being able to accurately anticipate the number of patients that will need care at a specific time and the level of care their conditions will require (Benton and Siferd, 1994) and appropriately schedule nursing staff to meet patient care demands is an even more difficult task. For example, at several times in the past three years MNCSD has closed down some nursing wards and transferred patients to other nursing wards in order to optimally utilize its available nursing personnel resources.

Several proposed solutions have been applied to this problem; and one of them is to increase in patient-to-nurse ratios, for which some researchers have found no clear evidence that such increases lead to higher nursing labor costs. A study conducted by Sovie and colleagues after the introduction of managed care found no relationship between skill mix on medical and surgical units and adjusted labor costs per patient (Sovie et al., 2000), while other studies conducted on the same subject found the opposite. In their article titled "Patients' Needs for Nursing Care: Beyond Staffing Ratios", Graf and colleagues found that the increase in complexity of care delivered to patients and the decrease in length of stay are of the reasons for the increased health care costs (Graf, Millar, Feilteau, Coakley, and Erickson, 2003).

Some researchers have found the increase in nursing labor costs to be created by the increased patient acuity and a higher demand for nurses in hospitals, forcing nurse wages to be upwardly impacted (Embleton et al., 2007) as more acute patients consume more nursing care hours than less acute patients. This in turn increases the overall patient length of stay, creating a greater variability in the nursing care needs of hospitalized patients (Welton et al., 2006).

Research suggests that a reasonable patient-to-nurse ratio may increase nursing personnel satisfaction and decrease the level of exhaustion of a nursing staff. A nurse that feels exhausted and burdened may desire to leave his or her job or may even neglect to document the care provided to the patients. Nurses with high workloads have a higher possibility of experiencing exhaustion and job dissatisfaction (Aiken et al., 2002). Good nursing staff scheduling thus reduces staff burnout and overload and increases patient safety.

D. LITERATURE REVIEW: NURSE STAFFING MODELS

The problem of determining future patient care requirements in order to appropriately schedule nursing staff has been a concern for nursing administrators all across the United States and the world. A nursing staff scheduling model that can help to reliably forecast the number of nurses that will be needed into the future is a good administrative tool which nursing administrators can use to do their nurse-to-patient ratio staffing planning. At the core of this problem are patient safety and nursing labor costs which hospital administrators have to reconcile by staffing their nursing units to a level that satisfies the optimal level of care delivered to their patients while minimizing the costs of nursing care (Heinz, 2004).

In order to cope with this problem, several nursing staff scheduling models have been developed. For example, Warner and Prawda (1972) propose a linear programming model in which they identify the staffing pattern as being specified by the number of nursing personnel of each skill class to be scheduled among the nursing units and nursing shifts and satisfying total nursing personnel capacity, integral assignments, and other constraints by minimizing a shortage cost of nursing care services provided by the scheduling period. Dale and Mable (1983) approach the nursing staff scheduling problem by using the Nursing Classification System (NCS) to introduce and illustrate the concept of workload indexing as a means of determining nursing staff needs and monitoring personnel workload and performance.

The model by Elkhuizen and colleagues on the capacity management of nursing staff considers historical bed utilization and nurse-patient ratios and tries to forecast the number of nurses needed for each nursing shift based on past available and non-available work hours, historical bed utilization, ward sizes, and nurse-patient ratios (Elkhuizen et al., 2007). Elliott and Kearns (1978) use simulation to predict the number of nursing personnel that will be needed at different points in time in the U.S. health care system. Bard and Purnomo (2005) propose an integer linear programming model by using the midterm schedule to address the problem of adjusting individual work assignments to account for daily fluctuations in the census levels, absenteeism of staff, and emergencies.

Other researchers, such as Rosenberger and colleagues, propose an information technology prototype for assigning nurses to patients by minimizing excess of workload on nursing personnel (Rosenberger et al., 2006). Siferd and Benton (1994) consider the nursing staffing scheduling problem as being a four-tiered decision problem:

- The long-term staffing decision, which is related to the hospital's mission, strategy, and competitive priorities-a decision made over a year or more.

- The intermediate term scheduling decision-a decision made every four to six weeks and which involves preliminary assignments of nursing personnel to the days and shifts to be worked.
- The daily allocation of nursing personnel to the nursing units and shifts where they are most needed.
- The actual assignment of a specific number of patients to a nurse on given nursing shift.

They further propose a scheduling model that considers the third tier or the daily allocation of nurses to the units and shifts in which, unlike most other nursing scheduling models that simply consider patient census and patient-to-nurse ratio, factors in the effects of both patient census and patient acuities.

E. DATA AND DATABASES

The data for this thesis project were pulled from several databases and repositories. The following is an abbreviated description of these databases.

1. The Composite Health Care System (CHCS) is the Department of Defense's comprehensive medical informatics and management system, providing operational support to Military Treatment Facilities (MTF's), mobile fleet hospitals, hospital ships, and other combat hospitals. CHCS standardizes disparate data such as laboratory data, standard insurance tables, appointments processing information, and First Data Bank and provides automated support to all areas of health care operations, including pharmacy, radiology, laboratory, managed care program, patient scheduling, patient administration, data administration, and nursing quality assurance. The Composite Health Care System supports clinical information sharing and interfaces with 55 other DoD computer systems, which include the Defense Enrollment and Eligibility Reporting System (DEERS), the Defense Blood Standard System (DBSS), the Integrated Clinical Database (ICDB), the Defense Dental Scheduling Application

(DDSA), the Clinical Information System (CIS), etc. For this thesis project data for ward census, discharges and patient transfers were pulled from CHCS.

2. The Res-Q software System is a labor management and employee scheduling software used in the management and scheduling of the nurse staff, patient acuity, and census at NCMSD. The Res-Q software includes applications for enterprise-wide employee scheduling, nurse scheduling, patient classification, productivity management, credentialing, operating room scheduling, and surgery department management. It helps in the management of health care productivity, cost control, and budget. Data for patient acuity or total required workload hours and performance index were pulled from Res-Q.

3. The Medical Expense and Performance Reporting System (MEPRS) code is a three-digit code, which defines the summary account and sub-account within a functional category in the Department of Defense (DoD) medical system. MEPRS codes are used to ensure that consistent expense and operating performance data are reported in the DoD military medical system. For instance, the MEPRS hierarchical arrangement, the MEPRS codes are as follows:

	MEPRS CODE
Outpatient Care (Functional Category)	**B**
Medical Care (Summary Account)	**BA**
Internal Medicine (Sub-account)	**BBA**

Table 1. MEPRS Code.

III. MODEL FORMULATION

This section discusses NMCSD nursing personnel requirements, describes time series modeling in general terms, and the Holt-Winter's time series model specifically.

A. NURSING PERSONNEL REQUIREMENTS

The future level of nursing personnel needed to meet workload requirements is not something that is normally known ahead of time, especially in a business environment like healthcare where demands for patient care may go up or down, depending on the month or the season of the year. DeWald (1996) describes this as an issue of two competing factors to any staffing problem that needs to be solved: available personnel versus required personnel (necessary to meet patient care requirements). Although unknown, as a matter of good personnel planning, the future level of personnel required for work can be predicatively estimated based on historical information on past patient census levels and their required nursing workloads.

In this thesis project, we estimated the past levels of nursing staff required to meet patient care demands in fiscal years 2005 thru 2007 in units of "full time equivalents" (FTEs) by dividing the total required monthly workload hours by 168 hours. According to DoD 6010.13-M, 1FTE per month = 168hrs. Given that total required monthly workload hours were adjusted in the Res-Q System for patient attributes and patient census, we assumed patient acuity and patient census are included the final results, which is a factor necessary to forecast future required nursing FTEs. Based on the description by Siferd and Benton (1994) – that nursing staff scheduling in an acute care hospital being a four-tiered decision problem – this model considers the first tier of the problem where monthly nursing staffing requirements are predicted one year into the future.

A useful place to begin is a historical comparison of required nursing staff levels to available nursing staff. Such a comparison is shown in Figure 1, from which the following important insights follow:

1. The hospital seems to have been historically over-staffed. However, because the data collected from the MEPRS database does not differentiate between more experienced nurses and nurses with less than one year experience, it is impossible to tell whether the "overstaffing" was the result of the addition of a number of new graduate nurses recruited into the hospital's nursing staff.
2. Starting in July 2006 or so, the overstaffing significantly decreased and the hospital currently shows that the number of required nursing FTEs and the number of FTEs used roughly match.
3. Although the number of required nursing FTE's and the number of available FTE's are different, the two graphs seem to follow an similar seasonal patterns, which is an assumption by the method.

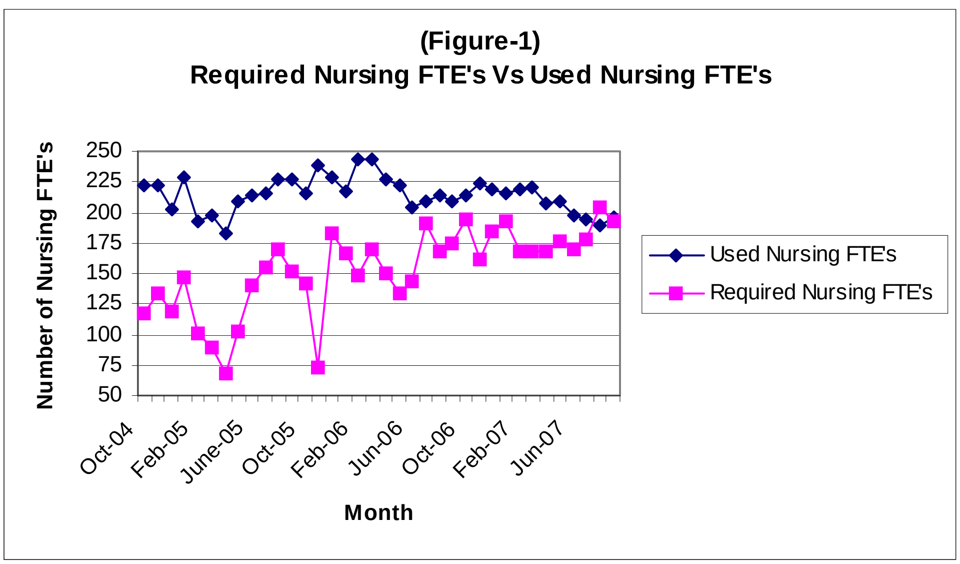

Figure 1. Required Nursing FTEs Vs. Used Nursing FTEs

B. TIME SERIES FORECASTING

Forecasting involves making probabilistic estimates and predictions about future values based on historical and current data (Kalekar, 2004). A forecast is basically a probabilistic estimate of future values (Frank et al, 2003), which help reduce the risk about an action of consequence, using information about possible outcomes (Kalekar, 2004). Several probabilistic models have been used to make predictions about future performance. Time series models are useful when data occur over time and past values of the outcome of interest are related to future values of the same outcome. Models using time series methods can help managers make prudent business decisions, provided that they exclude causal relationships and consider other business factors that may be associated with their decisions (Wheelwrigth & Makridakis, 1997), thereby avoiding such problems as inventory shortages and excesses, missed due dates, plant shutdowns, lost sales, lost customers, expensive expediting, missed strategic opportunities (Frank et al., 2003), and under staffing or overstaffing scheduling.

Time series models such as the Box and Jenkins model is suitable for data with non-stationary conditions or cyclical patterns and non-overlapping to make predictions (Klugh & Markham, 1985) while the Holt-Winters' models are useful for modeling data with trend and seasonality conditions (Kalekar, 2004).

Time series forecasts assume that the data occurs over time and is a combination of a pattern and some random error. The goal in using time series is to filter the pattern from the error by comprehending the trend of the pattern, its long-term increase or decrease, its seasonality, and the change produced by seasonal factors or fluctuations in use and performance (Kalekar, 2004).

The various types of time series models include moving average models, linear regression models with time incorporated, autoregressive moving average (ARIMA) models and exponential smoothing models. The choice of time series method depends on the behavior of the data being considered in the forecast model. In order to determine the condition displayed in the data, a pictorial assessment of the data needs to be made by graphing the data to determine if it displays stationary or linear conditions.

C. HOLT-WINTERS' TIME SERIES MODELS

Holt-Winters' models are one type of exponential smoothing time series model. Holt-Winters' models are designed for data having trend and seasonality fluctiations. In Figure 1, the data for available nursing FTEs and required nursing FTEs clearly display the trend and seasonality conditions making the model an appropriate choice for forecasting the monthly required nursing FTE's at Naval Medical Center San Diego.

To describe the Holt-Winter's model, we begin by describing the terms in the model. They are:

α = the smoothing constant for adjusting seasonality at the end of the month

β = the smoothing constant to calculate the trend

γ = the smoothing constant for calculating the seasonality index

Y_t = the number of actual nursing FTE's at the end of the month t

S_t = the smoothed value at the end of the month t after adjusting for seasonality

b_t = the smoothed value of the trend for the month t

I_{t-L} = the smoothed seasonal index L previous months

L = the length of the seasonal cycle (L = 12)

I_t = the smoothed seasonal index at the end of month t

m= the timeline of the forecasts of Y_{t+m}

Y_{t+m} = the actual number of FTE's of a series which is equal to a smoothed level value S_t plus an estimated trend b_t time a seasonal index I_{t-L+m}

The model can then be expressed as the following series of five equations:

$$S_t = \alpha(Y_t / I_{t-L}) + (1-\alpha)(S_{t-1} + b_{t-1}) \qquad \forall t \qquad 0 \le \alpha \le 1 \qquad (1)$$

$$b_t = \beta(S_t - S_{t-1}) + (1-\beta)b_{t-1} \qquad \forall t \qquad 0 \le \beta \le 1 \qquad (2)$$

$$I_t = \gamma(Y_t / S_t) + (1-\gamma)I_{t-L+m} \qquad \forall t \qquad 0 \le \gamma \le 1 \qquad (3)$$

$$Y_t = (S_t + b_t)I_{t-L} \qquad \forall t \qquad (4)$$

$$Y_{t+m} = (S_t + b_t m)I_{t-I+m} \qquad \forall t \qquad (5)$$

Equation (1) calculates the overall smoothing level of the series where the data is deseasonalized so that only the trend component and the prior number of FTE's of the permanent component get updated. Equation (2) calculates the adjusted trend deseasonalized at the end of month t. Equation (3) is the smoothed index, which estimates the seasonal component by combining the most recent observed seasonal factor given by Y_t divided by deseasonalized series and used to forecast values for one or more months ahead. Equation (4) calculates the actual number of FTEs of a series, which is equal to a smoothed level value S_t plus an estimated trend b_t times a seasonal index I_{t-L+m}. Equation (5) generates forecasts for months ahead.

The α, β, and γ parameters are fit via either the Excel Solver to minimize the Mean Absolute Percentage Error (MAPE). For example, for data with small random fluctuations or clear pattern larger α values help extrapolate the most accurate forecast near the most recent observed values, while small α values are better suited to smooth data with greater random fluctuation (Makridakis & Wheelwiright, 1978).

In this analysis, we used both JMP and Excel software packages to predict future required number of nursing FTEs per month, with the final result being the solution with the lowest MAPE if the two results from the two packages differ.

IV. RESULTS AND CONCLUSIONS

This section presents the results for an aggregate model of the entire hospital and five ward-level sub-models as well as a discussion of the results and some conclusions.

A. FULL HOSPITAL MODEL

The model with three parameters can be very effective (Frank et al, 2003), especially given the ability it allows to minimize the prediction error by choosing those parameters. Using the method with three parameters, we started by initializing the level, using the average number of FTE's for the 2005 fiscal year, trend with 0, and the season with the average of the FY 2005 FTEs with the level during the first month.

Using data from the Res-Q system, we fit Holt-Winters' models and extrapolated the monthly number of nursing FTEs that should have been used to meet patient care requirements (patient acuities and patient censuses combined) for the fiscal years 2005 thru 2007. Using both Excel and JMP software packages, the monthly number of nursing FTEs that would be needed for fiscal year 2008 in the entire hospital were forecasted. As shown in Table 2, we were able to forecast the monthly number of nursing FTEs required with an MAPE of 17.83.

Further analyses of the data, as pictured in Figure 3, led us to determine that, although not insignificant, the 17.83 MAPE might be caused by the three outlying data points in March 2005, April 2005, and November 2005. Consequently, we decided to bypass these three points by building our prediction model with historical data starting in December 2005. Averaging the data from December 2005 to extrapolate our first prediction in January 2007, the predictive values came out with an MAPE of 8.80, suggesting that the 2005 data was not useful for modeling later years of data.

Full Hospital Model	
Historical Data	**MAPE**
Starting October 2004	17.83
Starting December 2005	8.80

Table 2. Full Hospital Model

Figure 2 shows the monthly predicted FTEs for 2007 and 2008 along with the actual FTEs for later 2004 through September 2007. What Figure 2 shows is that the Holt-Winters' predictions are reasonable and consistent with the actual data in late 2007.

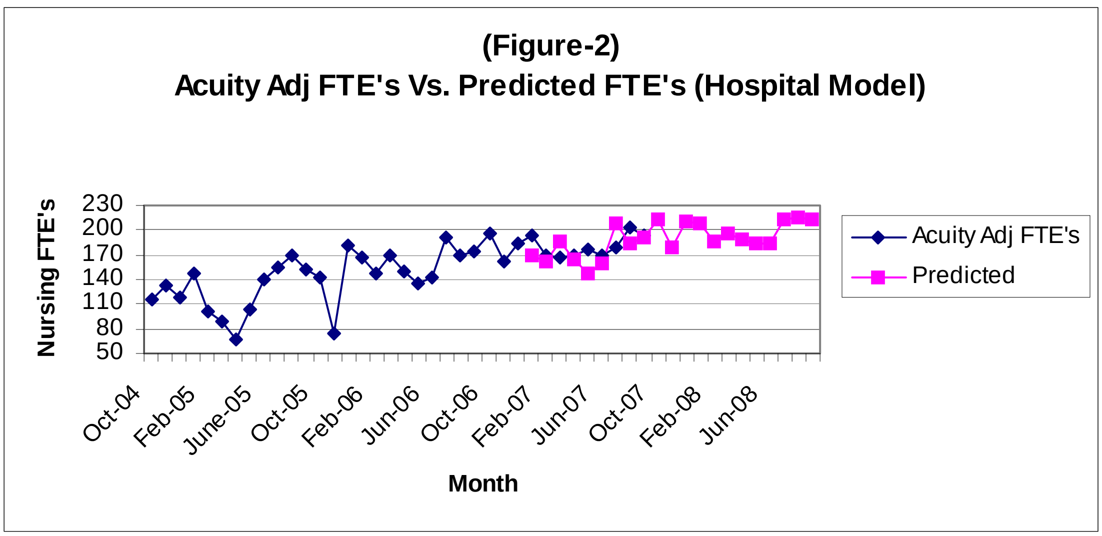

Figure 2. Acuity Adj. FTEs Vs. Predicted FTEs (Hospital Model)

B. WARD-LEVEL MODELS

Using the Holt-Winters' methodology, we also developed five sub-models for five nursing units (4West, Adult ICU, Surgical, Medical, and Medical Oncology). These nursing units were chosen because of the diverse types of nursing services they provide, the mix of patient types, and the combination of both experienced nurses and those with less than one year experience present.

As shown in Table 3 the MAPE's for 4West, Adult ICU, Surgical, Medical, and Medical Oncology are 35.57, 23.94, 85.81, 47.45, and 29.19 respectively. Further analyses of the actual data in Figures 3 thru 7 led us to eliminate the outliers of five sub-data sets and adjust for missing data points to arrive with a smoothed dataset for each sub-model. Doing that, we started the predictions with data for 4West in February 2006, for Adult ICU in January 2006, for Medical in June 2006, and for Medical Oncology in March 2006. As shown in Table 4, the monthly forecasts for these nursing units came out with an MAPE of 20.77, 11.42, 13.85, and 6.98 respectively. After adjusting the Surgical dataset for the numerous outliers, there were only four good data points left to make predictions, making it impossible to use the Holt-Winters' Seasonal Exponential Model. As a result, we used the Linear (Holt) Exponential Smoothing model, starting with data from June 2007. The model was fitted with an MAPE of 13.63.

Mean Absolute Percentage Error With Outliers		
Nursing Units	**Forecast Start Data**	**MAPE**
4West	Oct 04	35.57
Adult ICU	Oct 04	23.94
Surgical	Oct 04	85.81
Medical	Oct 04	47.45
Medical Oncology	Oct 04	29.19

Table 3. Mean Absolute Percentage Error With Outliers

Mean Absolute Percentage Error Without Outliers		
Nursing Units	**Forecast Start Data**	**MAPE**
4West	Feb 06	20.77
Adult ICU	Jan 06	11.42
Surgical	Jun 07	13.63
Medical	Jun 06	13.85
Medical Oncology	Mar 06	6.98

Table 4. Mean Absolute Percentage Error Without Outliers

Figures 3-7 show the monthly predicted FTEs for 2007 and 2008 along with the actual FTEs for later 2004 through September 2007. Except for Figure-5 where the Linear (Holt) Exponential Smoothing Model was used, what the figures show is that the Holt-Winter's seasonal predictions are again visually reasonable and consistent with the actual data in late 2007.

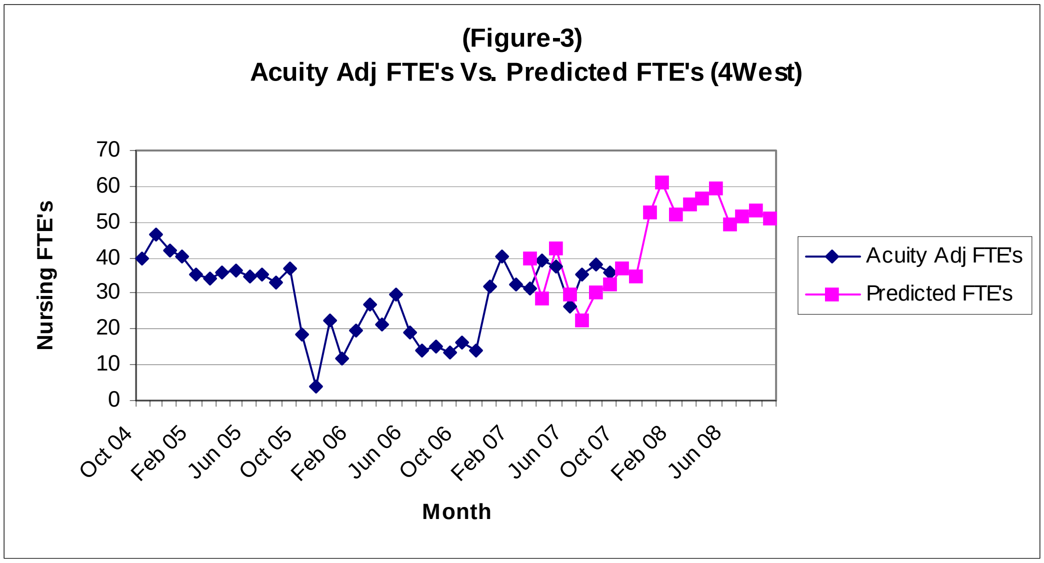

Figure 3. Acuity Adj. FTEs Vs. Predicted FTEs (4West Model)

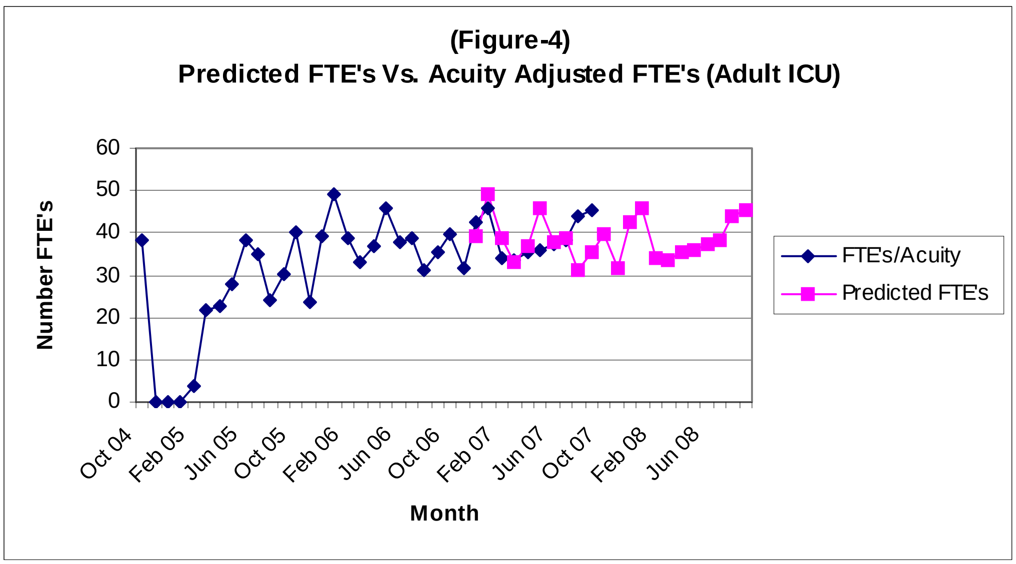

Figure 4. Predicted FTEs Vs. Acuity Adjusted FTEs (Adult ICU Model)

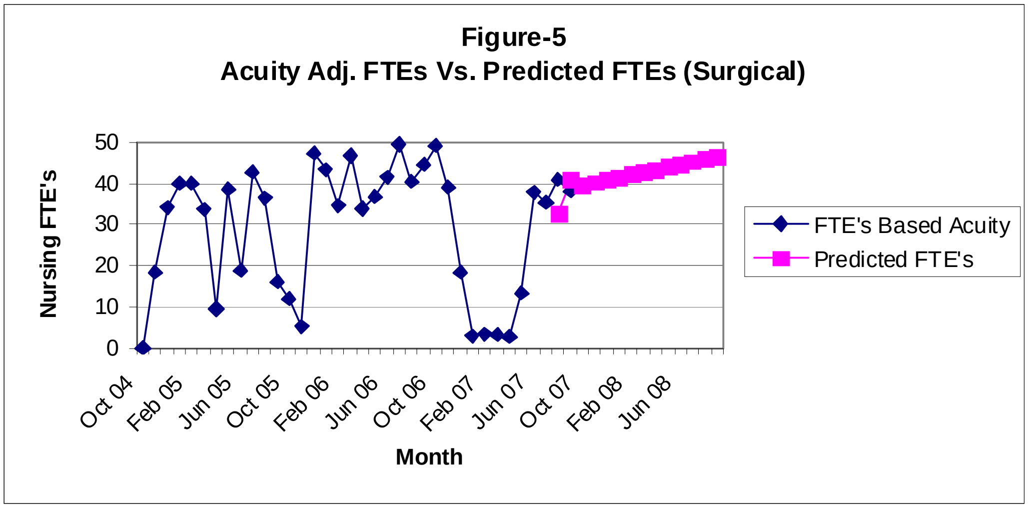

Figure 5. Acuity Adj. FTEs Vs. Predicted FTEs (Surgical Model)

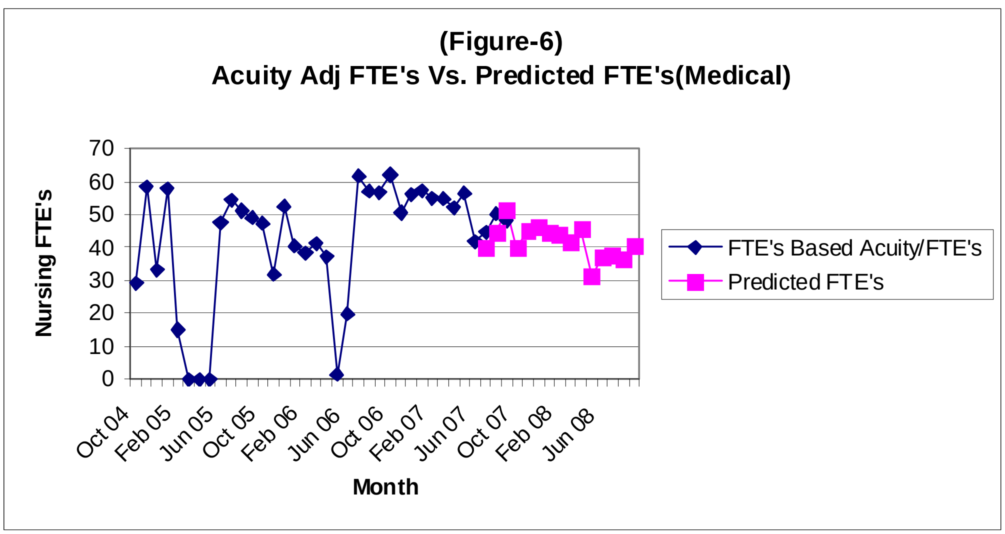

Figure 6. Acuity Adj. FTEs Vs Predicted FTEs (Medical Model)

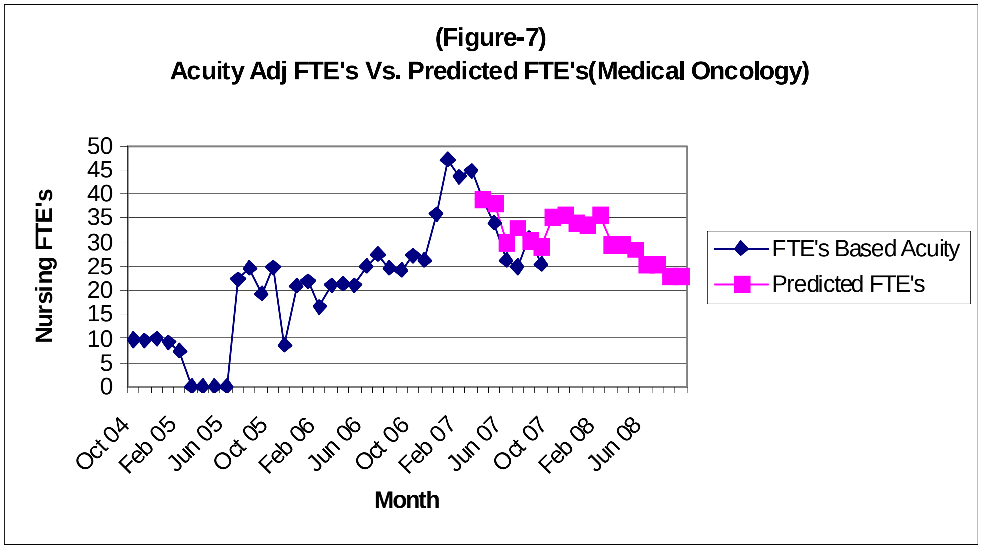

Figure 7. Acuity Adj. FTEs Vs. Predicted FTEs (Medical Oncology Model)

C. DISCUSSION

Based on the insights gained from this thesis project, there are three important points that need further emphasis. These are the forecasting model, the age of the data used to develop the forecasting model, and the possibly unforeseen mass disaster events that may occur in the future and which cannot be numerically predicted in the model.

The Holt-Winters' model, which is built to capture simultaneously the trend, the seasonality, and the cyclical changes in the historical data, may sometimes forecast future values that may have either an upward or downward trend, resulting in the same trajectory trend to continue further into the future. Just like the result shown in Table 2, suggesting that fitting data after adjusting for outliers will give a lower MAPE, it is also worth re-emphasizing that the appropriate type of predictive model depends on the shape of the historical dataset.

In terms of the data, modeling future values using historical data with multiple missing data points and outliers can be problematic. In our model we used data for the entire hospital; and this has given a very low MAPE. However, when modeling for the five nursing units, we have encountered a lot of noises in the model, with MAPEs ranging from 23.94 for 4West to 47.45 for Medical, and 85.81 for Surgical. We assumed that this problem was caused by missing data points and outliers in the sub-models as well as the multiple iterations by the software to find the most reliable forecasted values. When contacting our sponsor to find out about the reason for the missing data points and the outliers, we were told that it was based on policy decisions to consolidate multiple nursing wards to optimally use the available resources, especially during the times of unexpected low censuses.

The third important factor one has to consider when modeling future values is unforeseen mass disaster and other such unpredictable events. Because time series models predict the future based on the past, where such events presumably have not occurred, the model predictions do not allow for staffing for such events. Of course, these events must always be prepared for as a matter of good administrative planning. Furthermore, based on published standards by the Joint Commission on the Accreditation of Health Care Organizations (JCAHO) every accredited hospital is required to have an emergency preparedness plan designed to seamlessly intervene when unforeseen major disasters strike. However, the nursing staffing forecasts of this model cannot be used to make personnel planning decisions for unanticipated medical outbreaks.

D. CONCLUSIONS

The ability for decision makers to develop reasonable and dependable forecasts is paramount for the successful operations of any viable organization. It can help reduce risks about an action of future consequence and allow managers to make decisions about uncertain outcomes more intelligently. In an uncertain environment like healthcare, risky decisions have become more prevalent than ever. To this end using good mathematical tools can be very useful. One of the areas in health care that is most uncertain is future patient care requirements and the ability to schedule nursing FTEs to meet those requirements; for there are undoubtedly conflicting factors such as costs, patient safety, and personnel satisfaction associated with the decision of meeting patient requirements.

In order to tackle this problem, several nursing scheduling models have been developed. But all of the models we have found so far only focus on the short-term demands of nursing care. The nursing staff scheduling forecast model developed in this thesis project is different because it provides a long-term insight about the monthly number of nursing FTEs necessary to meet patient care requirements and it captures both patient census and patient acuity.

The method was used because a pictorial assessment of the dataset led us to assume that the number of nursing FTEs needed to offset patient care requirements is both seasonal and cyclical with an upward trend. The results of this analysis, using the Holt-Winters' method, gave a Mean Absolution Percentage Error of 17.83 for three years historical data and 8.80 for approximately two years of data. We then fitted models to ward-level data and predicted future required monthly nursing FTEs with a respective MAPEs of 20.77, 11.42, 13.85, and 6.98 for 4West, Adult ICU, Medical, and Medical Oncology. However, due to numerous outliers and missing data points in the Surgical dataset, we fitted the Linear (Holt) Exponential Model, using data starting June 2007. The MAPE for these forecasts was 13.63. Similarly to the other four ward-level models, the surgical ward model can be reverted back to Holt-Winter's seasonal model after a normal course of operations where there will be complete historical data available.

Our overall insights gained from this project lead us to conclude that the method can certainly be used to make nursing staff scheduling forecasts. However, in order to ensure reliable forecasted values, it is important to adjust the historical data for possible outliers and missing data points before developing the predictive model. In cases where the dataset displays numerous outliers, using a simpler model like Linear (Holt) Exponential Model will be more appropriate to forecast future values.

APPENDIX A: KEYWORDS AND ACRONYMS

This appendix provides additional information on various keywords, medical terminology, and acronyms used in this thesis.

A. PATIENT ACUITY

Patient Acuity is defined as the highest level of care that a patient with a certain ICD-9 code (diagnosis) will require based on the NMCSD established Performance Acuity Index. Patient acuity also considers a patient's condition, if the patient's medical prognosis is stable or unstable, and or if the patient is in a critical condition. For instance, two patients may have the same diagnosis, but if one patient's condition is more critical and less stable than the other's, that critically unstable patient will consume more resources than the patient whose condition is more stable. In this thesis we adjust total monthly required workload hours to reflect total required nursing full time equivalents needed to meet patient care based on patient acuities or required direct patient care hours and required indirect patient care hours.

Acuity can be explicitly defined as the maximum nursing care hours that will drive patient care requirements for a patient classified in one of the six levels of care. A patient classified in a greater range number of required hours of care or higher acuity level is considered more acute or more critical while a patient classified in a smaller range number of required hours of care or low acuity level is considered less critical or acute. The level of care is computed based on the different tasks of patient care a nurse performs, given a patient's diagnosis and condition. Those tasks are attributed a number of points where each point equals 7.5 minutes. The total points are then multiplied by 7.5 minutes, resulting in a range of nursing care hours required to treat that patient. The table below reflects the acuity levels, number of points assigned to those levels, and the number of hours of care required for the acuity level. The Naval Medical Center San Diego Acuity Index is based on the highest number of required hours of care in the 24-hour range.

Patient Acuity and Care Attribute Levels		
Acuity Level	**Points**	**Hours of Care/24hrs**
I	1-12	7.5”- 1.5hrs
II	13-21	1.6 – 2.5
III	22-63	2.6 – 7.9
IV	64-95	8 – 11.9
V	96-145	12 – 17.9
VI	146-262	18 – 32

Table 5. Patient Acuity Table

B. AVAILABLE FULL-TIME EQUIVALENT

Available Full-Time Equivalent (FTE) is defined in the Expense Assignment System (EAS IV) Repository User’s Guide as the amount of labor available for work. According to DoD 6010.13-M, one FTE equals 168 hours per month. Hence, in this thesis 168 hours will be used to calculate the number of required FTE’s needed to offset the Total Required Workload Hours.

C. ASSIGNED FULL-TIME EQUIVALENT

The Assigned Full-Time Equivalent represents those personnel who are on the facility’s staffing document (EAS IV Repository Guide, 2003).

D. TOTAL REQUIRED WORKLOAD HOURS

Total Required Workload Hours is the sum of all hours worked during the shift, both direct and indirect, as defined by the Skill Column activity in the Res-Q System. The following is an example of how Total Hours Required Workload is calculated:

- Direct Volume = Total volume (patients) X Budgeted HPPD (Hours Per Patient per Day)
- Total Volume = Direct Volume + Indirect care hours specified in the Staff Tab of the Budget Builder™
- Direct Workload = The sum of the number of patients in each category times the standard hours of care for the category plus the sum of each attribute times the standard hours for the attribute
- Direct Care Hours Worked = Sum of all direct care hours worked during the shift as defined by the Skill Column activity
- Total Hours Required Workload = Direct Care Hours Worked + Indirect Patient Care Hours Worked

E. PERFORMANCE INDEX

Performance Index is the quotient of the required nursing care hours divided by the actual number of hours of care provided to a patient. The NMCSD's target performance index ranges from 85% to 95%. A performance index less than 85% means that the hospital was over-staffed and performance index greater than 95% suggests that the hospital was under staffed.

F. CENSUS

Census is the number of patients admitted to a nursing unit starting at the midnight census counts and for more than 24 hours.

G. STAFFING TO CAPACITY

Staffing to capacity is the number of required number staff given that 80% of available beds are occupied.

H. PATIENT-TO-NURSE RATIO

Patient-to-nurse ratio is the number of patients assigned to a licensed nurse during a specific nursing shift. Studies conducted on this topic report that a reasonable patient-to-nurse ratio reduces the possibilities of patient adverse outcomes, nurse burnout, and increases job satisfaction. In 1999, the California legislature enacted legislation mandating a five-to-one patient-to-nurse ratio. The law went into effect in July 2003 (Aiken et al., 2002).

I. DIAGNOSTIC RELATED GROUPS (DRG)

Created under the Medicare prospective payment system (PPS) to control Medicare reimbursement costs, the DRGs classify all human diseases according to the affected organ system, surgical procedures performed on patients, morbidity, and sex of the patients and accounts for up to eight diagnoses in addition to the primary diagnoses and up to six procedures performed during a patient's hospital stay (OEI, 2201). According to the Office of Evaluation and Inspections of the Office of Inspector General, under the DRG reimbursement scheme, Medicare pays hospitals a flat rate per case for inpatient hospital care, giving hospitals the incentive to become more efficient by reducing a patient's hospital stay (OEI, 2201). The DRG final reimbursement to a hospital includes among other things adjustment for wage index factor in the area the hospital is located, adjustments for the DRG weight, disproportionate share payment, indirect medical education payment, and outliers (OEI, 2201).

J. LENGTH OF STAY (LOS)

Length of Stay (LOS) is the number of days of hospitalization a patient spends in a hospital. Under the Prospective Payment System, the government sets a maximum allowable number of days for each diagnosis for a patient with a particular DRG will normally spend in the hospital. Reimbursement is based on the full inpatient hospital services, including the intensity of the principal and secondary diagnoses, procedures, patient demographics, routine nursing services, room and board, and ancillary services (OEI, 2201).

APPENDIX B: NURSING STAFFING SCHEDULING REPORTS AND MODELS

Available Nursing FTEs and Acuity Adjusted Nursing FTEs					
Schedule Date	**perf_index**	**thrs_act**	**thrs_reqd_wrkld**	**Used Nursing FTEs**	**Required Nursing FTEs**
Oct-04	**0.7421**	26448.66	19627.03	**221.49**	116.83
Nov-04	**0.8997**	24824.14	22333.32	**222.51**	132.94
Dec-04	**0.7341**	27248.51	20003.46	**201.99**	119.07
Jan-05	**0.8181**	30291.79	24781.96	**228.23**	147.51
Feb-05	**0.8782**	19384.90	17023.73	**191.83**	101.33
Mar-05	**0.7746**	19428.84	15048.88	**197.97**	89.58
April-05	**0.6947**	16468.59	11440.90	**182.22**	68.10
May-05	**0.7216**	23958.83	17289.61	**208.72**	102.91
June-05	**0.7896**	29657.90	23416.55	**213.50**	139.38
July-05	**0.7168**	36237.32	25975.72	**215.72**	154.62
Aug-05	**0.7539**	37672.95	28402.02	**226.98**	169.06
Sept-05	**0.6927**	36898.07	25559.87	**227.34**	152.14
Oct-05	**0.8000**	29906.21	23925.80	**215.61**	142.42
Nov-05	**0.7874**	15632.58	12309.19	**237.89**	73.27
Dec-05	**0.7476**	40943.44	30608.46	**228.55**	182.19
Jan--06	**0.7845**	35601.20	27929.92	**217.64**	166.25
Feb-06	**0.7243**	34310.91	24849.70	**244.07**	147.91
Mar-06	**0.7758**	36577.67	28375.39	**244.16**	168.90
Apr-06	**0.6873**	36784.67	25280.67	**227.46**	150.48
May-06	**0.7150**	31580.87	22580.15	**222.87**	134.41
Jun-06	**0.7874**	30516.50	24027.80	**204.57**	143.02
July-06	**0.9053**	35503.00	32139.83	**209.48**	191.31
Aug-06	**0.7642**	37035.50	28302.02	**214.07**	168.46
Sept-06	**0.8361**	35070.65	29323.76	**208.85**	174.55
Oct-06	**0.8535**	38354.8	32734.64	**213.82**	194.85
Nov-06	**0.6924**	39197.2	27140.39	**224.10**	161.55

Dec-06	**0.7343**	42281	31046.67	**219.54**	184.80
Jan-07	**0.7745**	41933.8	32479.46	**215.12**	193.33
Feb-07	**0.7742**	36578.4	28320.42	**218.72**	168.57
Mar-07	**0.6924**	40639.8	28138.66	**220.36**	167.49
Apr-07	**0.7415**	38125.5	28268.67	**207.98**	168.27
May-07	**0.7276**	40871.5	29739.49	**208.35**	177.02
Jun-07	**0.7210**	39435.3	28431.87	**197.48**	169.24
Jul-07	**0.7708**	38840.5	29939.84	**194.62**	178.21
Aug-07	**0.8536**	40048	34184.64	**188.91**	203.48
Sep-07	**0.8276**	39183.8	32430.14	**195.35**	193.04

Table 6. Available Nursing FTEs and Acuity Adjusted Nursing FTEs

Full Hospital Forecast Model								
Observed Values		**Holt-Winters' Expo Smoothing Model**						
Schedule Date	**Acuity Adj FTE's**	**Level**	**Trend**	**Season**	**Predicted**	**Error**	**Percent Error**	**JMP-Prediction**
Oct-04	**116.83**	122.08	0.00	0.96				
Nov-04	**132.94**	122.08	0.00	1.09				
Dec-04	**119.07**	122.08	0.00	0.98				
Jan-05	**147.51**	122.08	0.00	1.21				
Feb-05	**101.33**	122.08	0.00	0.83				
Mar-05	**89.58**	122.08	0.00	0.73				
April-05	**68.10**	122.08	0.00	0.56				
May-05	**102.91**	122.08	0.00	0.84				
June-05	**139.38**	122.08	0.00	1.14				
July-05	**154.62**	122.08	0.00	1.27				
Aug-05	**169.06**	122.08	0.00	1.38				
Sept-05	**152.14**	122.08	0.00	1.25				
Oct-05	**142.42**	122.08	0.00	1.17				
Nov-05	**73.27**	122.08	0.00	0.79				

Dec-05	**182.19**	117.56	-0.40	1.32	114.27	67.93	37.28	
Jan--06	**166.25**	120.29	-0.12	1.31	145.20	21.05	12.66	
Feb-06	**147.91**	121.14	-0.04	1.07	100.52	47.39	32.04	
Mar-06	**168.90**	123.78	0.20	1.12	90.97	77.93	46.14	
Apr-06	**150.48**	128.16	0.56	0.93	71.81	78.67	52.28	
May-06	**134.41**	133.74	1.01	0.94	113.59	20.82	15.49	
Jun-06	**143.02**	135.98	1.11	1.09	156.52	13.50	9.44	
July-06	**191.31**	136.25	1.04	1.35	173.87	17.44	9.11	
Aug-06	**168.46**	137.96	1.10	1.29	192.57	24.11	14.31	
Sept-06	**174.55**	137.84	0.99	1.26	173.01	1.54	0.88	
Oct-06	**194.85**	138.81	0.99	1.31	163.08	31.77	16.30	
Nov-06	**161.55**	141.16	1.11	1.01	112.82	48.73	30.17	
Dec-06	**184.80**	145.07	1.35	1.29	193.74	8.93	4.83	
Jan-07	**193.33**	145.88	1.31	1.32	193.33	0.00	0.00	168.86
Feb-07	**168.57**	147.07	1.30	1.11	158.27	10.31	6.12	162.48
Mar-07	**167.49**	148.80	1.33	1.12	167.49	0.00	0.00	185.41
Apr-07	**168.27**	150.01	1.32	1.05	140.89	27.38	16.27	163.24
May-07	**177.02**	152.77	1.45	1.07	145.13	31.89	18.01	147.89
Jun-07	**169.24**	155.87	1.59	1.09	171.21	1.97	1.16	159.73
Jul-07	**178.21**	157.21	1.57	1.22	214.33	36.11	20.26	209.12
Aug-07	**203.48**	156.86	1.40	1.29	203.48	0.00	0.00	184.96
Sep-07	**193.04**	158.14	1.39	1.24	200.75	7.71	4.00	191.64
Oct-07		159.03	1.35	1	210.11			212.19
Nov-07				2	162.66			179.10
Dec-07				3	210.91			210.70
Jan-08				4	217.14			207.30
Feb-08				5	184.81			186.04
Mar-08				6	187.45			196.27
Apr-08				7	176.29			187.69
May-08				8	182.18			184.26
Jun-08				9	185.94			184.88
Jul-08				10	210.28			213.70

Aug-08				11	224.74			215.07
Sep-08				12	216.48			213.04

Table 7. Full Hospital Forecast Model

	4 West Model								
	Total Req.	**FTEs Based**	**Holt-Winters' Expo Smoothing Model**						
Month	**Workload Hrs**	**Acuity Adj. FTE's**	**Level**	**Trend**	**Season**	**Predicted FTEs (Excel)**	**Error**	**Percent Error**	**Predicted FTEs (JMP)**
Oct 04	6632.78	39.48							
Nov 04	7786.73	46.35							
Dec 04	7022.59	41.80							
Jan 05	6784.01	40.38							
Feb 05	5887.85	35.05							
Mar 05	5750.38	34.23							
Apr 05	6045.80	35.99							
May 05	6156.92	36.65							
Jun 05	5800.19	34.52							
Jul 05	5971.71	35.55							
Aug 05	5506.41	32.78							
Sep 05	6255.37	37.23							
Oct 05	3106.81	18.49							
Nov 05	624.03	3.71							
Dec 05	3783.75	22.52	18.65	0.00	1.21				
Jan 06	1957.95	11.65	18.65	0.00	0.62				
Feb 06	3304.4	19.67	18.65	0.00	1.05				
Mar 06	4514.19	26.87	18.65	0.00	1.44				
Apr 06	3542.26	21.08	18.65	0.00	1.13				
May 06	4943.4	29.43	18.65	0.00	1.58				
Jun 06	3213.71	19.13	18.65	0.00	1.03				
Jul 06	2336.96	13.91	18.65	0.00	0.75				
Aug 06	2571.38	15.31	18.65	0.00	0.82				
Sep 06	2285.6	13.60	18.65	0.00	0.73				
Oct 06	2766.23	16.47	18.65	0.00	0.88				
Nov 06	2385.32	14.20	18.65	0.00	0.76				

Dec 06	5341.63	31.80	18.65	0.00	1.21	22.52	9.27	49.71	
Jan 07	6770.89	40.30	20.00	0.39	0.62	12.74	27.56	137.84	
Feb 07	5449.03	32.43	28.10	2.66	1.05	32.43	0.00	0.00	
Mar 07	5226.32	31.11	30.76	2.66	1.44	48.13	17.03	55.35	39.63
Apr 07	6545.25	38.96	31.35	2.05	1.13	37.75	1.21	3.85	28.70
May 07	6260.13	37.26	33.58	2.10	1.58	56.30	19.04	56.68	42.48
Jun 07	4406.95	26.23	33.58	1.49	1.03	35.96	9.73	28.97	29.51
Jul 07	5920.56	35.24	33.41	1.00	0.75	25.66	9.58	28.69	22.62
Aug 07	6352.54	37.81	36.65	1.66	0.82	31.44	6.38	17.40	30.41
Sep 07	6043.21	35.97	39.67	2.06	0.73	30.43	5.54	13.96	32.45
Oct 07			43.05	2.45	1.00	40.16			37.10
Nov 07					2.00	36.50			34.83
Dec 07					3.00	60.84			52.43
Jan 08					4.00	33.01			60.93
Feb 08					5.00	58.29			52.15
Mar 08					6.00	83.16			55.14
Apr 08					7.00	68.02			56.49
May 08					8.00	98.78			59.47
Jun 08					9.00	66.73			49.32
Jul 08					10.00	50.35			51.59
Aug 08					11.00	57.41			53.15
Sep 08					12.00	52.81			51.09

Table 8. 4 West Model

	Adult ICU Model								
			Holt-Winters' Expo Smoothing Model						
Month	Total Req.	Acuity Adj. FTEs	Level	Trend	Season	Predicted FTE's(Exl.)	Error	Percent Error	Predicted FTE's (JMP)
Oct 04	6430.22	38.28							
Nov 04	0.00	0.00							
Dec 04	0.00	0.00							
Jan 05	0.00	0.00							
Feb 05	665.18	3.96							
Mar 05	3652.92	21.74							
Apr 05	3805.82	22.65							
May 05	4665.03	27.77							

Jun 05	6453.31	38.41							
Jul 05	5891.52	35.07							
Aug 05	4057.24	24.15							
Sep 05	5119.03	30.47							
Oct 05	6715.04	39.97	37.44	0.00	1.07				
Nov 05	3994.07	23.77	37.44	0.00	0.64				
Dec 05	6588.12	39.21	37.44	0.00	1.05				
Jan 06	8239.38	49.04	37.44	0.00	1.31				
Feb 06	6486.10	38.61	37.44	0.00	1.03				
Mar 06	5553.86	33.06	37.44	0.00	0.88				
Apr 06	6221.18	37.03	37.44	0.00	0.99				
May 06	7660.90	45.60	37.44	0.00	1.22				
Jun 06	6322.36	37.63	37.44	0.00	1.01				
Jul 06	6487.57	38.62	37.44	0.00	1.03				
Aug 06	5238.15	31.18	37.44	0.00	0.83				
Sep 06	5969.61	35.53	37.44	0.00	0.95				
Oct 06	6683.22	39.78	37.44	0.00	1.07				
Nov 06	5293.64	31.51	37.44	0.00	0.64				
Dec 06	7159.71	42.62	37.44	0.00	1.05	39.21	3.40	7.98	
Jan 07	7696.09	45.81	37.44	0.00	1.31	49.04	3.23	7.06	52.45
Feb 07	5736.20	34.14	37.44	0.00	1.03	38.61	4.46	13.07	37.02
Mar 07	5667.85	33.74	37.44	0.00	0.88	33.06	0.68	2.01	29.35
Apr 07	5969.32	35.53	37.44	0.00	0.99	37.03	1.50	4.22	36.55
May 07	6036.53	35.93	37.44	0.00	1.22	45.60	9.67	26.91	44.37
Jun 07	6234.23	37.11	37.44	0.00	1.01	37.63	0.52	1.41	30.19
Jul 07	6409.46	38.15	37.44	0.00	1.03	38.62	0.46	1.22	36.27
Aug 07	7347.95	43.74	37.44	0.00	0.83	31.18	12.56	28.71	30.21
Sep 07	7614.92	45.33	37.44	0.00	0.95	35.53	9.79	21.61	44.52
Oct 07			37.44	0.00	1.00	39.97			49.37
Nov 07					2.00	23.77			41.10
Dec 07					3.00	39.21			51.23
Jan 08					4.00	49.04			57.69
Feb 08					5.00	38.61			46.80
Mar 08					6.00	33.06			43.84
Apr 08					7.00	37.03			46.55
May 08					8.00	45.60			51.18
Jun 08					9.00	37.63			48.01
Jul 08					10.00	38.62			49.09
Aug 08					11.00	31.18			48.13
Sep 08					12.00	35.53			50.86

Table 9. Adult ICU Model

SURGICAL Model					
	Performance	Total Req.	Available	Nursing FTEs	
Month	Index Acuity	Workload	FTE's	Acuity Adj. FTEs	JMP-Prediction
Oct 04	0.00	0.00	57.09	0.00	
Nov 04	0.98	3087.55	65.05	18.38	
Dec 04	0.77	5743.92	51.51	34.19	
Jan 05	0.78	6719.33	58.74	40.00	
Feb 05	0.86	6696.23	49.92	39.86	
Mar 05	n/a	5645.58	45.99	33.60	
Apr 05	n/a	1589.28	46.96	9.46	
May 05	n/a	6467.66	53.93	38.50	
Jun 05	n/a	3152.08	48.75	18.76	
Jul 05	n/a	7184.62	50.98	42.77	
Aug 05	0.77	6115.26	52.83	36.40	
Sep 05	0.74	2693.85	57.53	16.03	
Oct 05	0.82	1989.28	48.09	11.84	
Nov 05	0.82	870.00	55.83	5.18	
Dec 05	0.81	7927.57	52.35	47.19	
Jan 06	0.81	7259.36	47.31	43.21	
Feb 06	0.73	5817.97	58.57	34.63	
Mar 06	0.67	7836.38	58.66	46.65	
Apr 06	0.81	5676.88	50.72	33.79	
May 06	0.70	6181.98	46.39	36.80	
Jun 06	0.73	6967.43	37.59	41.47	
Jul 06	0.82	8311.76	40.70	49.47	
Aug 06	0.93	6776.82	44.77	40.34	
Sep 06	0.75	7473.97	46.67	44.49	
Oct 06	0.93	8259.69	47.75	49.16	
Nov 06	0.82	6548.57	50.16	38.98	
Dec 06	0.31	3081.03	42.80	18.34	
Jan 07	0.00	487.60	45.90	2.90	
Feb 07	0.49	575.02	45.05	3.42	
Mar 07	0.40	528.15	40.25	3.14	
Apr 07	0.00	445.20	42.82	2.65	
May 07	0.53	2239.85	41.53	13.33	
Jun 07	0.77	6355.70	35.95	37.83	
Jul 07	0.65	5912.73	37.24	35.19	
Aug 07	0.80	6843.76	40.90	40.74	32.55
Sep 07	0.72	6400.59	34.19	38.10	40.83
Oct 07					39.56
Nov 07					40.19
Dec 07					40.83

Jan 08					41.46
Feb 08					42.10
Mar 08					42.74
Apr 08					43.37
May 08					44.01
Jun 08					44.64
Jul 08					45.28
Aug 08					45.91
Sep 08					46.55

Table 10. Surgical Model

Medical									
	Total Req.	FTE's Based	Holt-Winters' Expo Smoothing Model						
Month	**Workload**	**Acuity/FTE's**	**Level**	**Trend**	**Season**	**Predicted FTE's**	**Error**	**Percent Error**	**JMP-Prediction**
Oct 04	4921.69	29.30	33.0375	0	0.88674				
Nov 04	9848.01	58.62	33.0375	0	1.77432				
Dec 04	5562.12	33.11	33.0375	0	1.00213				
Jan 05	9722.01	57.87	33.0375	0	1.75162				
Feb 05	2513.92	14.96	33.0375	0	0.45293				
Mar 05	0.00	0.00	33.0375	0	0				
Apr 05	0.00	0.00	33.0375	0	0				
May 05	0.00	0.00	33.0375	0	0				
Jun 05	8010.97	47.68	33.0375	0	1.44334				
Jul 05	9167.1	54.57	33.0375	0	1.65164				
Aug 05	8601.27	51.20	33.0375	0	1.54969				
Sep 05	8256.54	49.15	33.0375	0	1.48758				
Oct 05	7960.1	47.38	33.038	0	1.43417				
Nov 05	5349.92	31.84	33.038	0	0.9639				

Dec 05	8804.01	52.40	33.038	0	1.58622				
Jan 06	6782.68	40.37	33.038	0	1.22204				
Feb 06	6445.2	38.36	33.038	0	1.16123				
Mar 06	6934.32	41.28	33.038	0	1.24936				
Apr 06	6252.65	37.22	33.038	0	1.12654				
May 06	242.133	1.44	33.038	0	0.04363				
Jun 06	3312.97	19.72	33.038	0	0.5969				
Jul 06	10390.71	61.85	33.038	0	1.8721				
Aug 06	9581.35	57.03	33.038	0	1.72628				
Sep 06	9523.21	56.69	33.038	0	1.7158				
Oct 06	10442.49	62.16	33.038	0	1.88143				
Nov 06	8506.15	50.63	33.038	0	1.53256				
Dec 06	9434.25	56.16	33.038	0	1.69977				
Jan 07	9614.42	57.23	33.038	0	1.73223				
Feb 07	9249.53	55.06	33.038	0	1.66649				
Mar 07	9203.49	54.78	33.038	0	1.6582				
Apr 07	8783.11	52.28	33.038	0	1.58246				
May 07	9478.47	56.42	33.038	0	1.70774				
Jun 07	7035.66	41.88	33.038	0	1.26762				
Jul 07	7516.32	44.74	33.038	0	1.35422	61.85	17.11	38.24	**39.92**
Aug 07	8436.52	50.22	33.038	0	1.52001	57.03	6.81	13.57	**44.73**
Sep 07	8097.82	48.20	33.038	0	1.45899	56.69	8.48	17.60	**51.36**
Oct 07			33.038	0	1	62.16			**39.83**
Nov 07					2	50.63			**45.36**
Dec 07					3	56.16			**46.43**
Jan 08					4	57.23			**44.26**
Feb 08					5	55.06			**43.98**
Mar 08					6	54.78			**41.48**
Apr 08					7	52.28			**45.62**
May 08					8	56.42			**31.08**
Jun 08					9	41.88			**36.78**

Jul 08					10	44.74			**37.62**
Aug 08					11	50.22			**36.36**
Sep 08					12	48.20			**40.55**

Table 11. Medical Model

Medical Oncology Model									
Month	**Ttl. Req. Wkld Hr**	**Acty Adj. FTEs**	**Level**	**Trend**	**Season**	**Predicted FTE's(Exl.)**	**Error**	**Percent Error**	**JMP-Prediction**
Oct 04	1642.34	9.78							
Nov 04	1611.03	9.59							
Dec 04	1674.83	9.97							
Jan 05	1556.61	9.27							
Feb 05	1260.55	7.50							
Mar 05	0.00	0.00							
Apr 05	0.00	0.00							
May 05	0.00	0.00							
Jun 05	0.00	0.00							
Jul 05	3732.48	22.22							
Aug 05	4121.84	24.53							
Sep 05	3235.08	19.26							
Oct 05	4154.57	24.73							
Nov 05	1471.17	8.76							
Dec 05	3505.01	20.86	19.82	0	1.05239				
Jan 06	3690.55	21.97	19.82	0	1.1081				
Feb 06	2796.03	16.64	19.82	0	0.83952				
Mar 06	3536.64	21.05	19.82	-8E-16	0.8881	17.61	3.45	16.37	
Apr 06	3587.7	21.36	23.02	0.7565	0.89677	21.32	0.04	0.17	
May 06	3551.74	21.14	23.81	0.7642	0.89486	21.99	0.85	4.00	
Jun 06	4211.33	25.07	23.79	0.5798	0.92954	22.66	2.41	9.62	
Jul 06	4612.83	27.46	26.51	1.0859	0.95276	26.29	1.17	4.25	
Aug 06	4134.32	24.61	28.6	1.3247	0.93258	27.91	3.30	13.41	

Sep 06	4071.37	24.23	27.01	0.6346	0.92483	25.57	1.34	5.51	
Oct 06	4583.01	27.28	26.46	0.3529	0.94802	25.42	1.86	6.82	
Nov 06	4406.71	26.23	28.43	0.7357	0.94249	30.69	4.46	17.01	
Dec 06	6030.05	35.89	28.07	0.4757	1.01598	31.63	4.27	11.88	
Jan 07	7910.46	47.09	34.13	1.7991	1.09545	30.16	16.92	35.94	
Feb 07	7310.64	43.52	41.74	3.1751	1.08391	39.89	3.63	8.34	
Mar 07	7512.85	44.72	40.99	2.2461	1.08546	38.77	5.95	13.30	
Apr 07	6525.79	38.84	41.56	1.8489	1.05251	38.84	0.00	0.00	**38.98**
May 07	5724.51	34.07	38.06	0.5809	1.01818	35.91	1.84	5.40	**38.29**
Jun 07	4399.33	26.19	34.38	-0.427	0.96213	32.35	6.16	23.53	**29.95**
Jul 07	4180.77	24.89	28.41	-1.741	0.94331	24.87	0.02	0.06	**33.06**
Aug 07	5203.87	30.98	26.43	-1.797	0.99326	22.78	8.19	26.45	**30.31**
Sep 07	4273.6	25.44	30.03	-0.519	0.90786	27.97	2.54	9.97	**29.26**
Oct 07			28.28	-0.81	1	26.05			**35.24**
Nov 07					2	25.89			**35.62**
Dec 07					3	27.09			**34.21**
Jan 08					4	28.32			**33.54**
Feb 08					5	27.15			**35.78**
Mar 08					6	26.31			**29.72**
Apr 08					7	24.66			**29.44**
May 08					8	23.03			**28.50**
Jun 08					9	20.98			**25.25**
Jul 08					10	19.81			**25.44**
Aug 08					11	20.05			**23.02**
Sep 08					12	17.59			**22.94**

Table 12. Medical Oncology Model

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